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Simulation-based Strategies for Smart Demand Response

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ABSTRACT

Demand Response can be seen as one effective way to harmonize demand and supply in order to achieve high self-coverage of energy consumption by means of renewable energy sources. This paper presents two different simulation-based concepts to integrate demand-response strategies into energy management systems in the customer domain of the Smart Grid. The first approach is a Model Predictive Control of the heating and cooling system of a low-energy office building. The second concept aims at industrial Demand Side Management by integrating energy use optimization into industrial automation systems. Both approaches are targeted at day-ahead planning. Furthermore, insights gained into the implications of the concepts onto the design of the model, simulation and optimization will be discussed. While both approaches share a similar architecture, different modelling and simulation approaches were required by the use cases.

KEYWORDS

Smart grids, Demand response, Modelling and simulation, Energy efficiency in industry, Smart buildings, Industrial energy management, Heating and cooling control, Optimization.

INTRODUCTION

Policy makers around the world pursue different strategies in order to successfully combat climate change and preserve our planet for future generations. Strategies such as

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the United States' Climate Action Plan or the European Union's Energy and Climate Package commonly feature targets concerning reduction of greenhouse gases, integration of renewable energy sources and improvement of energy efficiency. In order to achieve these goals, a combination of measures targeting energy production, storage, and use must be applied. Facing the challenge of integrating renewable energy sources, strategies to balance energy use and production are called for. Therefore, intelligent Demand Side Management and Smart Grids connecting energy suppliers and users are crucial for success.

Demand Side Management is often defined as planning, implementation, and monitoring of utility activities designed to influence the customer's use of energy [1]. According to Palensky and Dietrich [2], Demand Side Management measures can be distinguished into different categories according to their timing and impact. On one end of the spectrum, improvements in energy efficiency deliver permanent reductions and are therefore the most desired form of Demand Side Management. Dynamic Demand Side Management or Demand Response (DR) is designed to reduce the energy demands at certain critical times but may result in higher overall demand due to rebound effects and have a higher impact on the energy user's processes. Nevertheless, facing the need to balance volatile renewable energy generation with modified load profiles, the demand for DR strategies is evident. Therefore, DR has become an emerging field of research in recent years with a rapidly growing number of publications [3]. However, despite a number of studies that have proven the positive impact of DR [4], market integration is still quite low [5, 6]. Kim and Shcherbakova [6] identifies a number of barriers for successful implementation. On consumer side these include, among others, availability of technology, consumer knowledge, and response fatigue due to frequently changing prices. These findings suggest that there is a need for technological solutions which enable consumers to participate in DR programs in a way that requires little or no human effort. According to Siano [7], these enabling technologies include demand reduction strategies optimized to minimize various objective functions and their integration into the building energy management system.

Literature offers a number of solutions to the problem of demand reduction strategies for a wide range of application cases. Some interesting approaches include agent-based strategies [8], Model Predictive Control (MPC) of building climate control [9], linear programming approaches for intra-day demand optimization of small businesses [10], or simulated annealing approaches [11]. According to Deng *et al*. [12], most DR approaches share that they are usually formulated as an optimization problem and the user behaviour is mathematically modelled. Prívara *et al*. [13] stresses that the choice of model is a crucial part for a predictive control problem. This statement is transferable to many other simulation-based optimization problems, since modelling can be a tedious and time-consuming task.

This paper presents two different concepts to integrate demand-response strategies into energy management systems in the customer domain of the Smart Grid. The first approach is set out to achieve load shifts by an optimized use and integration of thermal storage masses in buildings into the urban energy management. To realize this goal, a method based on MPC was developed. The goal of the second approach is to improve energy efficiency in industrial production by developing a simulation-based tool for monitoring, predicting and optimizing the energy and resource demands of manufacturing facilities. The tool will be integrated into industrial automation systems, such as Enterprise Resource Planning (ERP) or Manufacturing Execution Systems (MES), and will introduce energy demand as a steering parameter into the control centre. Considering time scales, both approaches are targeted at day-ahead planning and are designed to be fully integrated into the consumer's automation system, and thus are potentially suitable for integrating communication flows with other domains of the Smart Grid, as intended, for instance, by the EU's Smart Grid Conceptual Model (see [14]).

After describing the concepts, the two projects will be compared concerning implications on the system architecture, the model and simulation design, and the optimization algorithm.

MODEL PREDICTIVE CONTROL OF HEATING AND COOLING

The goal of the project presented in this chapter was to maximize the share of renewable energy sources for covering the energy demand in urban areas. Previous investigations had demonstrated that 100% coverage of the electrical energy demand in a city district by means of fluctuating renewables over a year is in principle possible [15]. The project sets out to converge to this goal by tapping load shift potentials through integration and optimized use of thermal, electrical and passive storage masses in buildings into the urban energy system management. In order to achieve this, a design for optimized control strategies, based on MPCs was developed. The predictive control algorithm was combined with accurate models and predictions of the development of energy demand, production, consumption, as well as weather-related forecasts into a simulation framework. In a subsequent step a hardware-in-the-loop application with the real building was implemented.

An office building located in Vienna, which offers about 5,000 m² office space, was chosen as a reference object. The building, called EnergyBase, features a design, which renders it ideally suitable for the successful application of load shifting strategies. It is fulfilling the passive house standard and the innovative building design includes large Thermally Activated Building Systems (TABS).

Figure 1 illustrates the structure of the Heating, Ventilation and Air Conditioning (HVAC) system for room conditioning. Two sources provide heating: a ground water operated heat pump and a solar thermal system on the rooftop. Ground water provides cooling energy as well. Heat and cold are injected into the rooms via thermally activated building systems (concrete cores), which are arranged along four lines, supplying the cores of all floors in each quadrant (NW, NE, SW, SE). The temperature is controlled by a state-of-the-art room temperature control, which generates set points for the desired TABS temperature for each floor and zone as a function of the current ambient temperature. Furthermore, the cooling power used for air conditioning is supplied by a desiccant cooling system regenerated by heat from the solar thermal system.

The goal was to test the model predictive control approach in two steps, first by conducting a test-simulation of the reaction and behaviour of the controlled building, and second by integrating the MPC into the real building. Considering the given building structure, the thermal storage potentials of the TABS seemed promising to hold load shift potentials, but the electrical demand should be shifted. Therefore, the heat pump and the ground water well pumps, which connect these two systems, had to be targeted. Both components represent large electric consumers, their electrical load for heat and cold production could be shifted to convenient times using the relatively inert system of the concrete cores. A similar concept was already investigated by [16].

With regards to the implementation of the MPC, the installed building control system imposed some restrictions upon the feasible interfaces. The only possible point to influence the installed control system was to modify the set point temperatures of the TABS and water in the supply line to the TABS. Due to these system peculiarities, the control path depicted by the MPC’s model included three parts: the HVAC system, the building thermal dynamics itself, and the control logic used to control HVAC devices based on set point and measured temperatures. The resulting model shows nonlinear and switching behaviour caused by discontinuous controllers and equipment with nonlinear characteristics. Furthermore, system complexity and availability of construction data suggested that a white box modelling approach was the most feasible option. In order to match these model characteristics and provide high control performance, a Modular Model Predictive Control (MMPC) approach was developed.

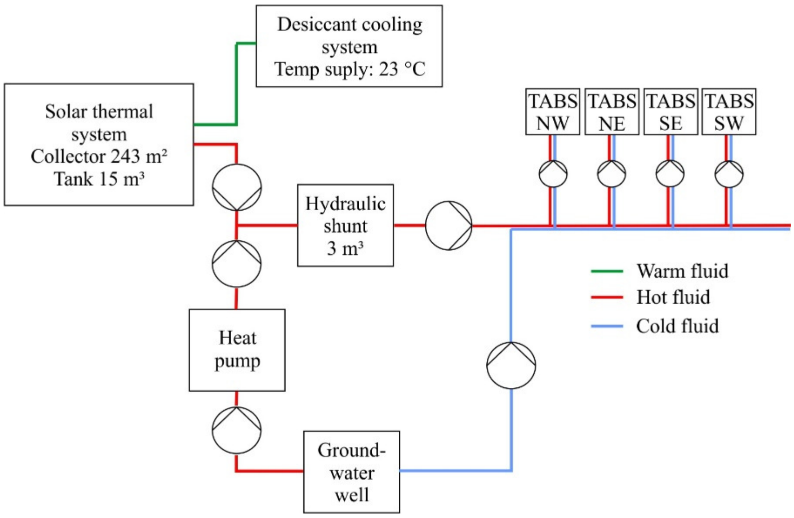

Figure 1. Overview of heating and cooling system at the ENERGYbase building (taken from [17])

The MMPC concept is based on a detailed model of the nonlinear dynamic building system, which is explained in further detail below. It is also designed to fulfil the requirements of real-time application and direct integration into the existing building control system by providing TABS temperature set point trajectories, which allows for retrofitting the existing building control system. The MMPC concept obtains high control performance and robustness, while keeping the computational effort low in order to enable real-time control, by executing a three-step process. Exploiting the simulation results of the prediction model, the temperatures and heat flows of the building system are adjusted to optimize energy efficiency and thermal comfort based on a linear thermal model. Subsequently, using an efficient mixed-integer optimization step, the resulting heat flows are optimally mapped to the TABS temperature set point trajectories.

The MMPC is structured as depicted in Figure 2. In order to allow direct interfacing with the building's existing automation system, the MMPC outputs TABS temperature set points T_{set} as control signals. According to its name the MMPC consists of three functional modules, which are executed at each sampling step. The first module is a simplified nonlinear model of the building and building services (SBUI/SBS) and provides a baseline prediction of temperatures T_0 and heat flows $\dot{Q}_0$ in the building. The second module ($\dot{Q}$-adjustment) solves a Linear Time Invariant (LTI) MPC problem to adjust the heat flows, optimize the control objectives and obey control constraints. Finally, the third module (T_{set}-mapping) calculates the TABS set points by solving a mixed-integer optimization problem. This approach realized the optimized heat flows as close as the switching actuation behaviour caused by the control valves in the hydraulic distribution of the feed line allows. A more detailed description of the MPC can be found in [18].

The simplified model of the building itself (SBUI/SBS) was derived from plan data and simulation results of a more complex building model, which also served as a substitute for the real building in the MPC tests. The complex building model represents the building's thermal zones by RC networks as proposed by the "Beuken-model" approach [19], which offers a good balance between model quality and simplicity. But still the degree of complexity of the model caused troubles with regards to the application in an online optimization problem. Therefore, additional simplifications were carried out. The number of thermal zones in the building was reduced by aggregating the zones of the complex model in every floor into larger surrogate zones. The acausal modelling approach used in the complex model to calculate heat flows in the building model and mass flows in the hydraulic system, was substituted by a simplified signal-based approach.

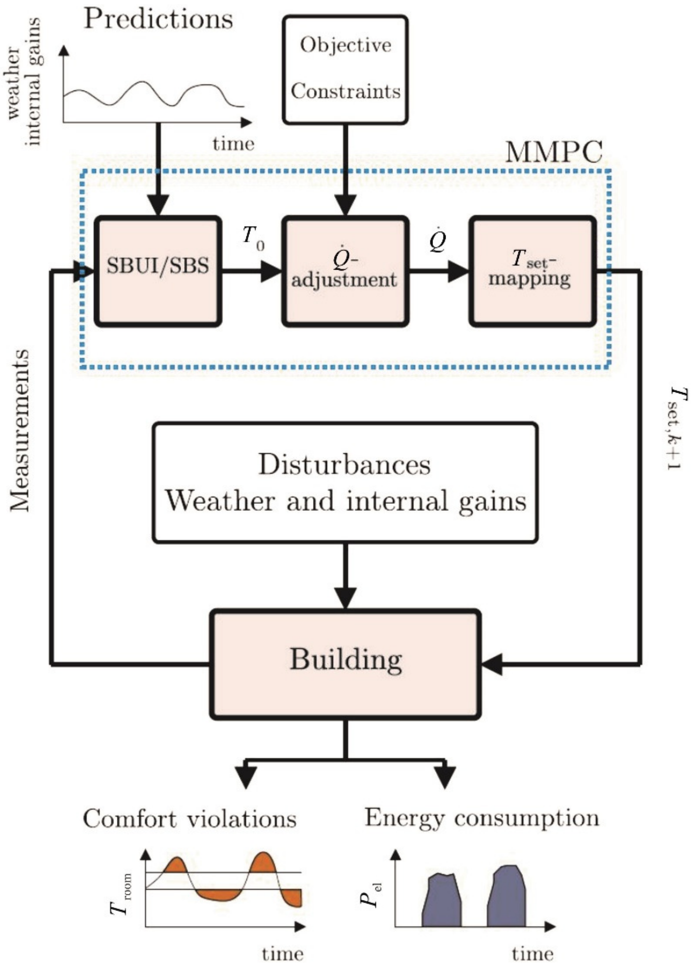

Figure 2. Structure of the MMPC building integration (taken from [18])

To model the hydraulic system of the building services, a causal model mapping only the energy flows, was used. This approach eliminates the necessity to calculate the state of the fluid at every relevant system point of the hydraulic system but raises additional challenges. Temperatures at the relevant points, often used as feedback for control of the hydraulic system, are not calculated anymore. Alternative approaches to approximate the control strategies based on the temperatures of thermal capacitances integrated into the system (e.g. storage tanks, TABS) had to be developed. Applying the described model reductions decreased the number of non-trivial model equations by a factor of 1/20 from the complex to the simplified model and the simulation time shortened correspondingly. Detailed descriptions of the complex and the simplified model as well as the implementation and validation of results can be found in [17, 20].

For the implementation of the test-simulation and the hardware-in-the-loop application, a sequential co-simulation approach using MATLAB as a master was chosen. MATLAB initializes simulation runs of the simplified Dymola model (SBUI/SBS or module 1) when needed. After completing the simulation run over the prediction horizon (in this case 48 hours), a baseline prediction of temperatures T_0 and heat flows $\dot{Q}_0$, calculated by the simulation in Dymola, are returned to MATLAB where adjusted heat flows $\dot{Q}$ and set-point temperatures T_{set} are calculated by modules 2 and 3. The set point temperatures for the next time step $T_{set,k+1}$ are then communicated by MATLAB to the building automation system. In order to calculate the baseline prediction of temperatures and heat flows, predicted weather and user behaviour data is used.

The optimization problem, which calculates the heat flows $\dot{Q}$, is presently oriented at minimizing the electric energy demand over the prediction horizon without violating the thermal comfort. It would, however, be feasible to minimize not the electricity demand but the electricity costs by introducing a time-variant weight into the cost function. By implementing an interface to market or operator and regularly updating energy cost predictions (e.g. once a day to cater to the day-ahead market) similar to weather predictions, an entirely autonomously working DR system could be realized.

INDUSTRIAL ENERGY MANAGEMENT

The manufacturing industry is one of societies' largest energy consumers and promises major potentials concerning demand reduction and load shift. Paulus and Borggrefe [21] estimates that Demand Side Management stemming from large-scale industrial plants might provide approximately 50% of capacity reserves for the positive tertiary balancing energy market in 2020. The authors of the study, however, also emphasize that industrial contribution to negative reserves (e.g. by shutting off equipment) is not feasible, due to potential disruption of production processes. Though it may be difficult to contribute negative reserves within the short time span required by the balancing energy market, a longer planning horizon (e.g. targeted at the day-ahead market) could open the possibility to schedule processes according to energy market requirements.

Therefore, in the second project the idea to develop a software solution enabling companies to integrate energy-related planning into their operative business emerged. Outlining the research question quickly showed that a tool chain has to possess certain features in order to present a feasible solution to the problem. Firstly, it has to integrate both ecological as well as economical parameters as optimization targets because in the end economic success is always the critical factor in a company. Secondly, a comprehensive approach addressing all parts of the system has to be chosen because the determining factor is the energy demand of the whole company, not only of subsystems. Thirdly, since the aspired solution should introduce energy considerations into the plant's operational planning, it has to be linked to the existing automation systems. And finally, if a prediction of the energy demand should be made and optimized, some sort of mathematical model and an optimization algorithm have to be included.

Finding a suitable method for model development was one of the core challenges. This is because although the tool chain may be an almost entirely reusable software solution, the model within the software tool chain represents a unique plant. Such a plant must be modelled from scratch for every specific instance and the modelling process represents a considerable effort. Only a certain degree of model reusability can reduce this effort.

Reusability can be achieved through decomposition and modularization approaches at the model design level. Such approaches seem to be a promising solutions for medium to large scale simulation models [22-24]. Similar design principles are applied in object-oriented software engineering, where encapsulation and information hiding play an important role in addition to modularization and decomposition. With encapsulation, communication between individual parts of a model only takes place via interfaces. This hides internal details from the external, only providing necessary functionalities and properties. As long as the interfaces remain unchanged, the resulting models of system parts can be exchanged without affecting the overall system behaviour [25]. These findings suggest that developing a modelling approach based on decomposition and encapsulation could lead to an efficient modelling framework for our task.

From the system analysis perspective, the chosen method must be designed to address the high system complexity and heterogeneity. The system modules serve to organize the knowledge base for individual modelling tasks by providing a concept for depicting elementary parts of a manufacturing system that contribute to its resource balance and their possible structural relationships.

Therefore, the chosen approach relies on basic modules that compose the system. In the project's context the modules are called "cubes". Cube boundaries bundle balances in terms of energy, material, cost and information flows. Although cube boundaries are imaginary, in most cases they will coincide with some sort of physical representation. A cube can be, for instance, an assembly robot, a gas heater, a conveyor belt, the production hall or a utility system. By specifying these modules, the system can be decomposed into observable parts. Defining the cubes by a boundary specification enables encapsulation and information hiding and therefore a combination of different modelling approaches and degrees of model abstraction. It furthermore ensures the compatibility of simulation models across various domains (production machines, building, energy supply, etc.) of the plant and applicability in various industrial sectors.

Figure 3 shows the overall system architecture. On the lower right, the real system, decomposed into imaginary cubes, is shown. The real system and the plant's automation system interact via sensors and actuators, which produce measurement data and apply control actions. Additionally, the automation system routes data from sensors, Enterprise Resource Planning (ERP) or Manufacturing Execution Systems (MES) to the software tools and the real system, therefore integrating the tool chain into the control centre.

The tool chain is designed to support production planning processes. Similar to a production planning and scheduling system, the planner can import upcoming orders to be scheduled as well as energy related data, such as weather forecasts or energy prices. Monitoring data from the real system supplies initial values. The tool chain calculates optimized production schedules and infrastructure operation strategies, such as ideal time slots for energy storage charging. These optimized production and operation strategies have to be confirmed by the user to be put into operation. The tool chain itself produces the results via interaction of an optimization algorithm and the simulation model based on cubes. The implementation of both is explained in more detail below.

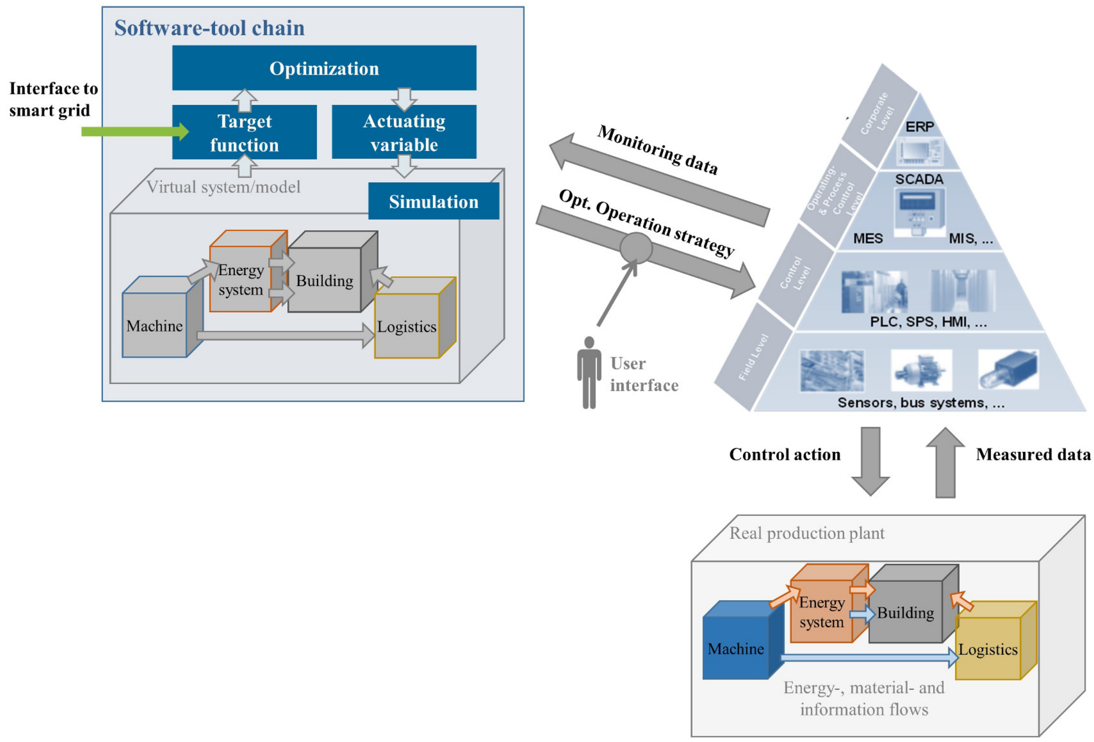

Figure 3. System architecture for the proposed tool chain (taken from [17])

The generalized interfaces ensure the cubes' general applicability and therefore offer a lot of advantages, however also causes one of the biggest challenges. In order to represent economic and ecological parameters, energy flows, which are continuous by nature, and value streams, which are described as discrete entities, must be integrated into one cube. This leads to hybrid cube models, which combine discrete-event and continuous simulation aspects, i.e. they are described by differential and algebraic equations as well as state machines. In order to be able to integrate both simulation models in each model module (cube), an approach for integrated hybrid simulation instead of using e.g. co-simulation (like in the MPC approach) is pursued. A more detailed description of the modelling method has been published in [17].

After evaluating different formalisms and descriptions for hybrid simulation, Discrete Event and Differential Equation System Specification (DEV&DESS) [26] as a hybrid Discrete Event System Specification DEVS formalism [27] based on Parallel DEVS (P-DEVS) [28] provided a suitable choice. The formalism is on the one hand open and established and on the other hand generic enough to allow incorporating different domains of engineering. Furthermore, a formal and complete description of hybrid model components and subsystems and transparent implementation of the simulation engine for handling events and equations is possible. Especially the second aspect is crucial in order to be able to include simulation functionality into the tool chain without having to rely on third party or proprietary software.

Using this formalism, simulation models are developed to represent the different aspects of the system under consideration. The models are used to make predictions about future energy demand of different operation scenarios. Furthermore, the simulation can also be used for complementary tasks such as the determination of a product footprint, as described in more detail in [29].

The simulation is coupled with an optimization algorithm, which is divided into two parts. In the first part, the production strategy of the considered plant is optimized. The degree of freedom for this optimization part is the production plan, i.e. the scheduling of the production plan for the different products that are going to be manufactured in the considered timeframe. Because of the hybrid model, on which the simulation is based, additionally to the conventional objectives such as costs, delivery reliability and the utilization of machines and storage, the energy consumption of the production plant for any given production plan can be considered for the target function.

In the second part, the energy system of the building is optimized. As the production plan of the facility is optimized in the first step, it is fixed for this part of the optimization. This means that the energy demands of the production are fixed and only the demand of the energy system itself is variable, a fact that can be exploited for the design of the optimization algorithm.

The degrees of freedom for this part of the optimization depend heavily on the model of the energy system. Typically this would mean that after modelling the system, the modeller would have to define them. But the cube concept enables a more automated way, as every cube used in the model can define its own Degrees Of Freedom (DOF), which can be congregated into the DOF of the overall model. Of course not every instance of a cube will have the same set of DOF, so it is important that the cube definition contains the maximum set of DOF for all applications and the active DOF for the particular instance of the cube can be enabled for the optimization. Possible degrees of freedom for some cube classes are:

- Energy networks and storages;
    - Set point level of energy storage;
    - Prioritization of energy sources;
- Energy converters;
    - On/Off-State of the machine;
- Thermal zones;
    - Set point temperature of the thermal zone.

As a small example consider a cooling network that is supplied by several chillers. Typically, such a system features a protected control algorithm supplied by the manufacturer which is integrated into the automation system of the operator, so the direct control of the chillers is not possible and therefore has to be disabled as a degree of freedom. Therefore, only variables accessible by the company's automation system, such as set point temperatures or prioritization, can be chosen as DOF. Considering only the prioritization of the chillers as sources for the cooling network, the number of different configurations gets very large as the number of chillers increases. This shows that the optimization algorithm has to be carefully designed in order to ensure maximum efficiency.

For the target function, different outputs of the simulation are considered:

- Total energy consumption;
- Total Carbon dioxide (CO_2) emission;
- Total energy costs;
- Share of renewable energy;
- Machine utilization;
- Share of heat recovery;
- Efficiency factor of the different energy types.

Depending on the use case, the weights of the components of the target function can be adjusted. Furthermore, constraints for the optimization must be generated. Examples for such constraints would be the requirement, e.g. that a certain room temperature has to be maintained for the comfort of the workers.

For the design of the optimization algorithm, multiple candidates exist. One notable restriction is that the algorithm has to be derivative-free since the simulation cannot return derivatives of the target function. The variables of the optimization of the energy system can be classified into two different classes:

- Continuous variables, such as target temperatures and levels as well as switching times for the machines;
- Scheduled variables, such as the prioritization of the sources for the energy networks.

For the scheduled variables, a graph-based algorithm can be considered, which would result in another division of the optimization algorithm, because the continuous variables would have to be optimized separately. Another possibility that enables the simultaneous optimization of the two variable types would be to map the scheduled variable on a set of continuous variables, where the sorted list of those variables defines the scheduling.

In practice, a combination of the two approaches looks feasible. Especially in systems where the demand from the production system (which is constant throughout the optimization) is very high, an initial tree search that is stopped at a certain level and a following optimization of the remaining scheduled variables and the continuous variables looks promising.

DISCUSSION OF METHODS

Although the two examples for simulation-based DR strategies target fundamentally different application fields (heating and cooling of an office building and industrial energy management) and levels of specification (one single application case vs. universal applicability to a certain sector), they show some similarities and highlight some implications the nature of the problem has on the mathematical models behind the optimization task.

Upon close examination of Figure 2 and Figure 3, it can be seen that both approaches rely on the same basic structure (see Figure 4), as do many other examples found in literature, such as [3, 10, 12]. The automation system links the real system and the modelling and simulation unit, transferring e.g. sensor data for model initialization in one direction or control signals to the system. The simulation generates a prediction of the system behaviour using a model of the system. The solution is evaluated concerning certain criteria by a target or cost function. Based on the evaluation result, the optimization algorithm generates a new set of parameters with which the simulation is restarted. This iteration is repeated until convergence criteria are fulfilled. The link to the Smart Grid (be it the operator or the market) is modelled into the target or cost function, where certain amounts of energy consumed at certain times can be penalized or rewarded. Depending on the frequency of the execution of the optimization, the system dynamics and also the calculation speed of simulation and optimization, different planning horizons can be targeted.

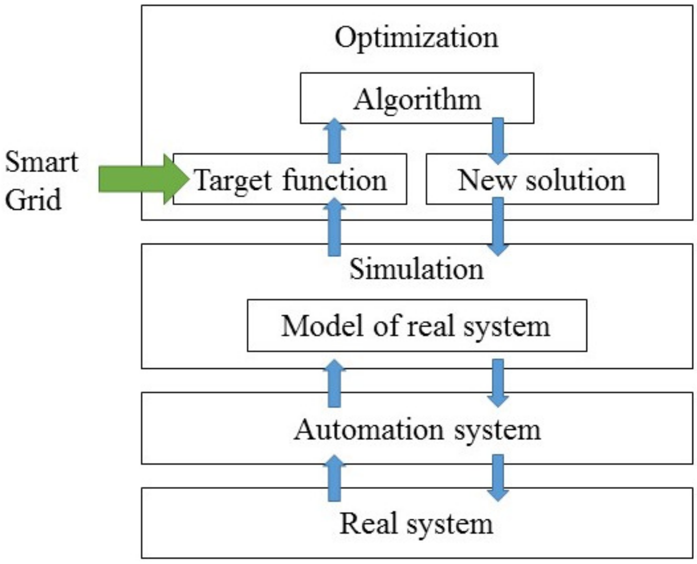

Figure 4. Generic system architecture

Another characteristic both approaches share at least at top level, is that a white box model turned out to be feasible. For the domain of building MPCs, Prívara *et al*. [13] supports the finding that physical models are preferable at least for simpler buildings. Similarly, building performance simulation tools fuse deductive modelling approaches at system level with inductive approaches at component level [30]. This approach reflects that components, although of varying characteristic according to type and manufacturer, are representations of the same basic concept, which can be implemented through inductive models, because they can depict an infinite number of variations by altering the parameterization. On the other hand, each system configuration is usually a unique solution and therefore the deductive approach fits well. Reflecting this system characteristics in the modelling method leads to a higher efficiency in model generation.

A distinguishing element of the two projects is the simulation implementation. While the MPC project was targeted at a single implementation, the energy management project is designed to lead to a software tool chain applicable to many instances. This difference in life span leads to different interests concerning modelling and simulation. For a project with one single application, an inherent interest to reuse pre-existing models and simulation tools exists in order to reduce modelling effort. Accordingly, a co-simulation architecture was chosen to accommodate these interests. The tool chain has a considerably longer life span and needs to be highly modular, in order to be able to assemble new instances with limited effort, because every use case calls for a new model.

In this case the reusability of pre-existing models is less of an interest than the internal reusability of model parts or modules within the software tool chain. Therefore, for the second project an alternate approach, with very rigid decomposition into formalized modules is chosen. This eliminates the possibility for reuse of previously existing models or tools almost entirely and even calls for programming a tailored simulation environment. This effort only pays off because of the long life span and the gained internal reusability. Hence there is always a trade-off between reusability of existing elements and internal reusability, which must be reflected in the chosen modelling approach.

Concerning the design of the optimization, similar problems were encountered. In both approaches, the models used to predict the system behaviour raise certain challenges. In order to depict the system with sufficient accuracy, models of certain complexity are needed. Suitable optimization algorithms must be applied in order to deal with non-linear model behaviour or lack of available derivatives. For the MPC this problem is even more critical since it has to meet real-time requirements, which in this case means that one simulation and optimization cycle has to be concluded within 15 minutes. Therefore, only a limited number of simulation and optimization runs can be performed in order to calculate optimal results. In order to solve this problem, a specific MPC approach was developed. For the industrial energy management this problem is not as critical, since scheduling and planning usually takes place several days in advance and can take up more time, thus more time consuming meta-heuristic approaches can be applied to solve the optimization problem. However, in both cases it turned out to be beneficial to divide the whole optimization problem into parts.

A further point that caused considerable trouble in both projects was the determination of the degrees of freedom, or in other words the influencing factors on the automation system. Due to technical reasons, it is often not possible to actuate the desired equipment directly. In order to achieve the desired impact, secondary variables, such as set points, have to be influenced. These workarounds can have considerable impact on the model design, especially on which parts of the system have to be integrated into the model. Therefore, it is highly advisable to determine this interaction point in advance. Last but not least, a determining factor for the success of the integration of many sophisticated control and automation systems is the user acceptance, which should be ensured in early stages of the project.

For future work, expanding the targeted time frame for DR from day-ahead to shorter-term markets could be targeted. With the MPC approach this is possible in theory; for the industrial energy management tool, however, the challenge is steeper. Presently, due to the nature of the tool as a planning instrument, the targeted time span for DR must correlate with the planning horizon of the production and the reaction capabilities of the staff in charge. These constraints eliminate shorter target periods than day-ahead, as found in the requirement definition with industrial partners. Shorter-term DR would require different strategies, which:

- Do not touch the production processes;
- Operate in a more automatic fashion.

To solve this problem and target the short-term DR, the present system could be expanded into a multi-stage optimization. Maybe a fusion of the two approaches is a feasible solution.

CONCLUSIONS

This paper presents two different approaches enabling customers of Smart Grids to participate in demand response programs. They both include simulation-based demand control strategies optimized to meet different objective functions and their integration into the building energy management system of customers in the Smart Grid. The first concept presents a model predictive controller for heating and cooling of an office building and realizes load shifts in the building's electrical energy demand. The goal of the second example is to improve energy efficiency in industrial production by developing a simulation-based tool for monitoring, predicting, and optimizing the energy and resource demands of manufacturing companies. Both approaches are based upon simulation and optimization methods and are targeted at the day-ahead market.

The examples show some similarities and highlight some implications the nature of the problem has on the mathematical models behind the optimization task. They share a similar basic structure of interaction between simulation and optimization, interface with the automation system and the Smart Grid via target or cost function. Furthermore, both models are a combination of deductive and inductive modelling techniques reflecting the system's characteristics of a unique solution assembled from generic components. They, however, are designed for different life spans and therefore, call for different simulation and modelling approaches. The structure of the models and the interaction with the automation system require specific properties of the optimization algorithms and the degrees of freedom. There is also still an extensive demand of research concerning reduction of modelling effort, development of interfaces between systems supporting demand response on the customer side and the Smart Grid as well as the tapping of intra-day and regulation market DR potentials.

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